Social Academic Analytics in Higher Education

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Abstract. Social Academic Analytics (SAA) is proposed as a new scientific approach toward developing suitable instruments to promote virtual collaboration among participants in the higher education field. SAA refers to the process of extracting relational data for the purpose of exploring organizational structures within virtual learning organizations and knowledge networks. Implementation of SAA provides opportunities for organizers and instructors to optimize socio-technological infrastructures within (virtual) knowledge networks so as to encourage collaborative work, while offering significant potential for quality assurance. SAA combines theories and models from both informatics and the social sciences at the macro level in order to formulate data analysis for the field of (web-based) educational research. In this paper we introduce SAA and its constituent activities. Finally we select case studies and applications to compare analytical concepts from diverse disciplines and conclude with further suggestions as to how SAA concepts can be applied in educational data management.

Keywords: Learning Analytics, Social Academic Analytics, Social Network Theory, Dynamic Network Theory, Virtual Organization

1 Introduction

The paradigm of social network theory has been increasingly adopted in the context of educational sciences in recent decades. With the appearance of new theories of participatory forms of learning organization, the emphasis in educational sciences is moving toward relation-oriented descriptions of (socially) connected learning processes [1]. In the era of Digital Knowledge Communities (DKC), Open Educational Resources (OER), and Massive Open Online Courses (MOOC) a big challenge for organizers and administrators of (virtual) knowledge organizations and institutions is to offer emerging technologies for learning and organizational support. They have to keep in touch with their clients (students and/or faculties) to implement the right concepts in the right place at the right time, and they have to know what the actual social and socio-technological conditions are in order to set new benchmarks. In a network

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society organizers and instructors need to learn more about the handling of (large) relational data to answer the classic question of Lasswell (1948) anew [2]: »Who (and what) is connected to whom (and what) by which channels at which time with what effects?« Answers can be used to formulate strategy for highlighting patterns of collaboration and organizational performance indicators to improve learning environments. Social Academic Analytics (SAA) offers a new paradigm for collecting, extracting and monitoring »traces« [3] that participants leave behind. Our aim is to support organizers and administrators in academic education by providing analysis methods and technical instruments for strategic decision-making processes as well as a means for setting new benchmarks. SAA provides a wide range of implications for identifying strengths and weaknesses of (virtual) knowledge organizations.

2 Theoretical Background

2.1 Networked Learning Theory as New Paradigm

In education sciences the importance of knowledge communities and the increasing need for an improved web-based knowledge management were established first by Lave and Wenger (1991) with the communities of practice (CoP) approach in the early 1990's [4]. Rheingold (1993) discussed virtual communities as »social aggregations that emerge from the Net« [5]. Dillenbourg (1999) put forward »collaborative learning« as a new paradigm in educational contexts [6]. Haythornthwaite (2001) introduced the sociological network paradigm in educational research and highlighted the social aspects of learning [7]. Siemens (2004) introduced learning as a process of creating networks and established »connectivism« as the newest learning paradigm, urging that learning be based on »chaos, network, complexity, and self-organization theories« [1]. De Laat (2006) emphasized learning in networks, learning in teams, and learning in communities [8]. Thus, the new emphasis on relational and structural conditions in collaborative learning networks emerged as a major topic of many scientific studies.

2.2 A Relational Approach to Learning Analytics in Virtual Communities

Learning Analytics (LA) is widely defined as the »measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs« [9]. LA relates strongly to the fields of Educational Data Mining (EDM) and Business Intelligence (BI), at the »intersection of learning and information technology« [10]. Goldstein (2005) studied the uses of management information and technology in higher education, concluding that the time is right to devote attention to improving the technology infrastructure in support of academic analytics. »Institutions that want to succeed at academic analytics need to build their staff's capacity to understand data and perform analysis« [11]. Campbell & Oblinger (2007) described academic analytics (AA) as an »engine to make decisions or guide actions« to assist administrators' decision-making

[12]. However, AA as originally formulated does not transfer well to the Web 2.0 world of virtual educational environments, and it ignores the social relations among students, between students and teachers as well as among teachers. Ferguson and Buckingham Shum (2012) introduced the term Social Learning Analytics (SLA) as a subset of learning analytics [10]. SLA focused on how learners together build knowledge within online social and cultural settings. These authors were concerned primarily with the (degree of) success of individual learners. Recently there has been an increase in efforts to combine learning and academic analytics with social network approaches that move beyond individual learners to study the (degree of) success of virtual learning environments. Wellman (2012), a leading social network analyst, pointed out that the activities and engagement in the field of learning analytics require the birth of a new discipline [13].

3 The Key Concepts of SAA

Authors propose a new scientific specialty, Social Academic Analytics (SAA), in support of the development of suitable instruments for promoting virtual collaboration among the various types of entities or (as we will sometimes say) modes in the field of higher education: participants, resources, actions/tasks, locations/organizations, knowledge and/or events. We introduce SAA as a paradigm comprising four key activities: (1) extracting relational data from virtual higher education contexts; (2) using the data to explore those contexts; (3) monitoring social and learning activities; (4) and preventing unwanted outcomes. At the organizational level SAA refers to the process of extracting data from various entities for the purpose of exploring patterns of collaboration and structures within virtual organizations and knowledge networks as controlling instruments in decision-making processes. Virtual knowledge organizations such as we see in higher education [14] are describable as a multimodal network (see discussion of Table 2 below). SAA is as research technology capable of detecting hidden structures within virtual knowledge networks by means of applying its key activities of *extraction*, *exploration*, *monitoring*, and *prevention* so as to enhance interpretations of educational data systematically. Thus, (virtual) knowledge organizations can be studied as whole networks where the entity relationships are extracted from a macro perspective. SAA can be interpreted as a form of organizational analytics in (virtual) knowledge organizations (VKO) that allows the exploration of networks based on the presence or absence of connections between different types of entity.

3.1 Extracting relational data from virtual higher education contexts

VKO, such as E-Learning-Systems, Blended-Learning Systems, OER and MOOC structures consist of the various types of entities (or modes) that we have discussed above: participants (U), resources (R), actions/tasks (AT), localization (L), knowledge (K), and events (E). We introduced the systematization of entities and their relations based on Carley's (2003) multimodal entity concept called the meta-matrix [15]. The characteristics and attributes of entities and relations are strongly related to the research question. Relations between the entities are ubiquitous but often invisible; however, with the help of extraction methods relational data can be extracted and explored. Relational data on entities reflect, e.g., (social) participation, collaboration, communication, and/ or allocation. Analysis of these relations allows us to locate learner roles and network positions, community building processes, potential influentials, independent participants, technology clusters, concentration and capabilities of actions and tasks, communicative power, geospatial assessments, dominant knowledge, group talks and capabilities of resources, locations, trails, organizations, and events. To be able to handle relational data in such versatile higher-education contexts we recommend the use of Social Network Analysis (SNA), Dynamic Network Analysis (DNA), Semantic Social Network Analysis (SSNA), and Visual Analytics (VA). Table 1 maps applications to research questions and tasks.

Table 1. Extracting relational data from virtual higher education contexts

Entities in (virtual) knowledge organizations			Target	Using techniques
Participants (U)	Who?	Students, Educators, Faculties, Administrators,...	(Social) patterns of participation, collaboration, and communication, Roles/Positions, Potential influentials,…	SNA, VA
Resources (R)	What?	Courses, Materials, Social Media Tools, Publications,…	Allocation of technology clusters, Capability of resources,…	SNA, VA
Actions/ Tasks (AT)	How?	Read, Write, Share, Likes, Logged,...	Concentration and capability of actions/ tasks, Communicative power,…	SNA, VA
Localization (L)	Where?	Universities, Institutes, Research libraries, Journals,...	Geospatial assessments, Capability of locations and trails,…	SNA (Geospatial), VA
Knowledge (K)	What?	Content, Topics, Substances, Publications, Bibliographies,...	Hot topics, Knowledge congruence, Dominant knowledge, Group talks,…	SSNA, VA
Events (E)	When?	Start of term, Exam time, Logged in/out, Start/End of communication,…	Dominant events, Capability of events,…	DNA, VA

3.2 Using the relational data to explore those contexts

Relational data can be explored in matrices, edge lists, and /or sociometric graphs. With the help of Visual Analytics (VA) it is possible to explore and monitor networks as sociometric graphs according to best practices. For exploration and interpretation of relational data from multidimensional entities within (virtual) knowledge organizations, we revised the systematization of Carley's (2003) meta-matrix [15]. Table 2 shows the different types of networks that can be explored in (virtual) knowledge organizations.

Table 2. Systematization of networks in (virtual) knowledge organizations

	Participants (U)	Resources (R)	Actions/ Tasks (AT)	Localization (L)	Knowledge (K)	Events (E)
Participants (U)	*1. Social Learning Networks (SLN)*					
	Collaborative Learning	'Hybrid' Learning	Self-Regulated Learning	Distributed Learning	Knowledge Management	'Dynamic' Learning
Resources (R)	*2. Resource Management Networks (RMN)*					
	'Hybrid' Learning	Resource Management	Training & Needs	Resource Capability & Concentration	Information Distribution	Resource Development
Actions/ Tasks (AT)	*3. Interaction Networks (IN)*					
	Self-Regulated Learning	Training & Needs	Learning Design	Organizational Support	Training & Needs	Interactive Learning Processes
Localization (L)	*4. Organizational Networks (ON)*					
	Distributed Learning	Resource Capability & Concentration	Organizational Support	Organizational Structure (external)	Organizational Capability & K-Concentration	Organizational Performance
Knowledge (K)	*5. Knowledge Networks (KN)*					
	Knowledge Management	Information Distribution	Training & Needs	Organizational Capability & K-Concentration	Semantic Structures	Knowledge Flow
Events (E)	*6. Dynamic Networks (DN)*					
	'Dynamic' Learning	Resource Development	Interactive Learning Processes	Organizational Performance	Knowledge Flow	Innovation processes
Social Academic Analytics (SAA)						

The analysis of networks within (virtual) knowledge organizations is strongly related to the target of the analysis and the research questions. Activity, capacity, concentration, efficiency, performance, and flow processes can be explored and described by different configurations of entities. The configurations of entities in SAA are motivated by the potential connectivity among social (participants), technical (resources), action-based (actions and tasks), spatial (localization), content-based (knowledge), and chronological components (events). To explore the complex environmental conditions we classify the networks in (virtual) knowledge organizations as follows, where the numbers correspond to rows of Table 2: Social Learning Networks (1=SLN), Resource Management Networks (2=RMN), Interaction Networks (3=IN), Organizational Networks (4=ON), Knowledge Networks (5=KN), and Dynamic Networks (6=DN). For exploring social learning conditions and internal organizational structures within virtual knowledge networks the analysis of *Social Learning Networks* (SLN) is recommended. The exploration of *Resource Management Networks* (RMN) facilitates reflection by instructors and administrators on technology clusters, capabilities and concentration of resources, distribution processes, and resource development. The analysis of *Interaction Networks* (IN) describes the structural modalities for deployment of actions and tasks. *Organizational Networks* (ON) reflect intra- and inter-organizational aspects of (virtual) knowledge. *Knowledge Networks* (KN) display the organization and management of information and knowledge. Their analysis provides insights into semantic structures of knowledge and information within learning networks. *Dynamic Networks* (DN) arise from the aggregation of entities within (virtual) knowledge organizations on the basis of *time*. Study of evolution and temporal emergence is important to encourage instructors and administrators to promote innovation management and decision-making processes. The exploration of Dynamic Networks (DN) provide relational insights into dynamic learning mechanisms, resource developmental stages, interactive learning processes, organizational performances (internal and external), knowledge flow, and innovation processes.

3.3 Monitoring social and learning activities

Social learning networks (SLN) can be analyzed as multi mode networks with the help of relational software tools. We recommend ORA[1] as our preferred tool for analyzing and monitoring multimodal (dynamic) social learning networks. For monitoring and assessing organizational structures of social knowledge organizations, social resource aggregations, social learning behaviour and information management, inter-organizational structures, and social innovation and diffusion processes, SNA and DNA [16, 17] offer indicators and measurements to (a) observe patterns of participation and collaboration, (b) identify roles, positions, key entities and key groups, (c) reflect community building processes and group awareness effects, (d) study (independent) learning related to concentration and exclusivity of resources, knowledge, tasks, events, and learning group interactions, (e) observe technology use and resource sharing of agents and organizations in the learning network, and (f) extract overlapping knowledge bases and analyze changes over time. Typical indicators in SNA and DNA for monitoring conditions at the whole-network level (density of social ties, components, cliques, blocks, hierarchies, structural holes, fragmentation, and so forth; can be used for network classification, extraction of focus groups, and prediction indicators [16].

3.4 Preventing unwanted outcomes

For controlling and preventing unwanted outcomes, the examination of impacts, effectiveness, risks, and changes over time in organizational structures are highlighted in the literature [15, 17]. Visual Analytics (VA) supports statistical reports via control charts depicting changes and monitoring performance and capabilities in (virtual) knowledge organizations. Network structures and scenarios can be compared by continuous monitoring of network indicators. The examination of change in knowledge networks depends on parameters like decision intervals, probabilities, and the number of control networks to explain changing behaviour, to answer questions about whether and how knowledge can circulate in the knowledge organization, or whether some group members evolve as potential influentials [15]. The visualization of relational

[1] ORA is a dynamic meta-network assessment and analysis tool developed by Kathleen M. Carley of Carnegie Mellon University, http://www.casos.cs.cmu.edu/projects/ora/.

data provides an understanding of dynamics in social support, learning strategies, knowledge flow, and organizational developments by simulating and modeling relational data [17].

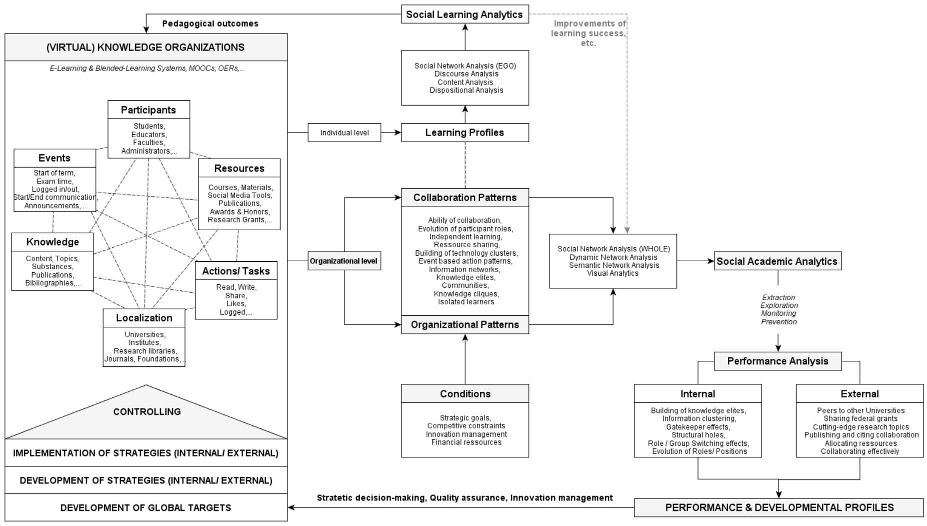

Fig 1. Social Academic Analytics: A Theoretical Framework

4 Case studies and applications in the area of SAA

A variety of case studies have applied one or more of the key components of the new analytic approach that we have set forth in the preceding section. In the longer and more complete version of our paper we review these case studies to highlight the ways in which they can inform the further development of a unified approach to SAA.

5 Conclusion: Future Directions

We have proposed Social Academic Analytics (SAA) as a new research specialty. With its focus on the four key areas reviewed above in Section 3, SAA highlights the need for a systematic way of exploring relational data within knowledge networks and can be considered as a strategic instrument in educational data management. SAA provides the concepts for building a clear understanding of the activities of entities, patterns of collaboration, organizational structures, and structural cohesion over time by implementation of dynamic modeling of (social) evolution for monitoring and preventing of unwanted outcomes. For future research we suggest the evaluation of SAA as concept in applied research. Answering the question »Who (or what) is connected to whom (or what) by which channels in which time with what effects?« is one of the major research problems that SAA can address. Applied studies of the spectrum of dynamics, competencies, capacities, requirements, and applicability are necessary for continuous improvements of SAA. We propose that software programmers in knowledge organizations should develop integrated (dynamic) techniques to handle relational data within a macro perspective, and combine SNA, DNA, SSNA, and VA as comprehensive applicable management software tool.

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